INTRODUCTION

Analysis of eeg signals using wavelets -some findings

In the field of EEG for neuropathology and disorders, there are quite many requirements. Some aim at EEG noise reduction for a better visual observational diagnostics. A fast wavelet transform for EEG, with a view to real time instrument observation, has been reported by Steven J. Schiff et al.,¹ (1994). Multi-resolution decomposition of EEG with a view to analyze local pathological patterns is very useful. A Wavelet-Like Filter Based on Neuron Action Potentials for Analysis was illustrated by Glassman² (2005). Apart from denoising³, another area has been in (automatic) identification of onset of spikes to aid in continuous patient monitoring.

EEG diagnosis primarily depends on visual observation of a chart or on the screen waveforms for an extended time (up to half an hour). While the signals themselves have stochastic or random content, patient artifacts and extraneous hum add to its complexity. The rhythmic signals of α,β, θ-activity etc are usually noticed in the records along with noise and background random signals even in a normal person. Patients suffering from some form of a brain injury also have only a similar pattern of signals except for short moments of abnormal activity of the waveform. So, after a continued period of background activity, the pathological signal may elicit on the records and may die down immediately or slowly. Such spikes, waves and their combination occur in varied patterns for various patients and from various electrodes. It is to look up for such signals only that ordinarily EEG records are taken over a long period of observation. The spike and wave patterns which are considered pathological when they have a higher amplitude than the background signal. Alternately it can be reasoned out that the spike and wave pattern

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S. ANANTHI*, V. Vidyadevi and K. Padmanabhan

Central Instrumentation Research and Department, University of Madras,
A.C Tech Campus, Chennai - 25 (India).

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ABSTRACT

Generally, EEG waveforms are recorded and observed for prolonged periods. The pathological findings are based on measurements of abnormal wave patterns which can appear once in a while. Wavelets is a useful technique of signal analysis which finds application for diagnosing EEG pathology. First, it is explained how Multi-resolution analysis is performed on wavelets to show up with a good match to the clinical bands of Alpha, beta, delta and theta rhythms in addition to waves and spikes. The appropriate choice of a wavelet is explained and the method indicated. Two method of displaying of wavelet analysis results are illustrated, one of plotting the maximal scale coefficients plot versus time; another of plotting the scale intensities versus scale value at a time point chosen for good EEG activity using the line of maxima in the scalogram figure. Comparative studies of a patient's records over a long period of observation can be easily made to assess the disease prognosis.

Key words: Stochastic signal, EEG Records, Photic stimulation, Fourier Transform, Wavelet Transform, Choice of wavelets.
characteristic of that pathology could exist with lesser amplitude and time (scale) even in the normal record and prior to the occurrence of the large amplitude pulse. In fact, it is common practice to stimulate the brain by photic or acoustic stimulation to elicit the spikes if such a pathology was lurking in a patient.

In other words, the abnormal characteristic pathology will reveal itself only by stimulation or after waiting on the record over an extended period of time. While stimulation is good in one sense in this way, it is not good for the patient himself because it disturbs the brain and for some cases of subdued grand or petit mal this may even provoke it. So it is clear that while the records themselves are indicative of the appropriate pathology either lurking or imminent, it is advisable to diagnose it directly as far as possible without stimulation. If we can observe the spikes and waves even from normal records, we may avoid stimulation whenever possible. In follow-up diagnostics, where repeated records taken over weekly or monthly periods are compared, stimulation is better avoided.

In this paper, a method using wavelet analysis is first described. While a sine wave based Fourier analysis is useful in analyzing periodic and time invariant phenomena, wavelet analysis is well suited to analysis of transient time varying signals. When we observe the pattern of the wavelet scalogram side by side with the EEG signal record, the correlations between values in the scalogram is very small and that leads to quicker identification of patterns. Voluminous amounts of such analysis have been performed on the full EEG records for many a patient and from these, certain excerpts which are based on multi resolution analysis are illustrated in the figures that follow. Characteristic patterns can be isolated from such lengthy records. Several wavelets are used and the results can be compared. From these, a suitable choice is made.

**Current methods for eeg analysis and interpretation**

Analyzing EEG records first and interpreting the same is the process of investigation. Visually analyzing the raw data and quantitatively examining the time series are the two methods that are available today.

In the first alternative, the complete EEG record, involving 16 to 32 channels of information and 20 to 30 minutes of recording, is examined visually by the clinical neurophysiologist. A short section of EEG record for a patient is illustrated in fig.1. This is a sample of an inter-ictal record with no stimulation. Like this, several records were obtained and analysed in this work. In the second method, analysis based on frequency patterns from time to time is performed. The record is first described for the present EEG periodicities, like the waveform itself, the amplitudes of it, the topographical distribution (which lobe of the head) and the changes in the regularity due to opening of the eyes, hyperventilation (deep breathing) and photic stimulation (using flashing bulb against the subject).

The main characteristics of the EEG are then described in a short text of about 200 to 400 words. The next phase is to decide whether the data is normal or that it indicates potential anomalies. If this is the case, then the type of abnormality is determined. The last step is to consider the relevancy of the EEG findings with respect to the clinical problem, that actually initiated the reason for the investigation. An answer must be given to a well-formulated clinical question. This requires neurological expertise. In most cases the EEG is considered to be a sensitive rather than a specific diagnostic instrument, making it a suitable instrument to monitoring the course of a disorder on the one hand and to determining a prognosis of the abnormality on the other. Specific forms of epilepsy (*absence epilepsy, hypsarrhythmia and benign focal epilepsy of childhood*) can be detected, but also *non-epileptic focal brain dysfunctions* possibly caused by cerebrovascular disorders, tumors, infections or traumas and *generalised brain dysfunction* in case of metabolic encephalopathy, intoxication, encephalitis or degenerative dementia are reflected by the EEG signal. Such defects can be classified as either occurring periodically or in a more continuous fashion.
Posttraumatic epilepsy and other causes of epilepsy by means of EEG scores is believed by physicians to be unsolvable.

Developing a new technology that could improve on analyzing and interpreting the EEG information definitely has a considerable contributing effect.

Using Wavelets For EEG Signal

Looking at the record (fig. 1) leads to one or more of the following inferences.

1. Mainly all waveforms are apparently random.
2. Spatial correlation is generally good in EEG signals.
3. Temporal correlation is absent over long periods.

This is one main reason for the data to get massive in size.

Also, the Fourier Spectrum also becomes meaningless for the same reason.

Had the waveform been a pure sine wave, then we will get a single coefficient to represent that. So, when we take the spectrum of an EEG, we do not normally get well defined limited number of peaks, but a noisy spectrum.

Early day EEG analysers had a Spectrum Analysis Channel in-built in the machine, using analog filters.

But that was useful only for very clearly seeing rhythm-signals, but not for pathological ones.

Herein we introduce the Wavelet based EEG Analysis. As stated above, in its various possibilities, let us examine typical wave records using wavelet analysis and observe the same.

Clinical EEG data from several types of patients were collected from the Government Hospital locally. These were available as actual computer-screen waveforms on several leads. The data were graphically digitized. Chart recorder EEG machines are not useful because they draw in a curvilinear pattern and hence digitizing the same will not be correct. Wavelet transform based programs were used to analyse certain segments of such data.

Fig. 1: Shows a sample EEG Record
Multi resolution plots
In a multiresolution analysis, the wavelet is decomposed into several scales and a plot each of the scale components is a waveform. (Fig 2). Scale is a term that is the reciprocal of frequency, with a factor that varies with the wavelet type. A low scale wavelet is a higher frequency wave than a higher numbered scale wave. Combining some scales and plotting the same with a view to eliminate high frequency components is also helpful. “Sig” shows the signal, “rec”, its reconstruction in this way. It is noted that the level ‘s3’ gives a signal which is indicative of the component wave that fluctuates. s1-s6 are scale numbers. The higher scale numbers are still lower frequencies.

![Waveform plots](image)

**Fig. 2:** A multi resolution analysis of a signal shows the predominant component at some scale or other

The scale which gives the maximum amplitude at any instant of time, — not maximum in the average sense — is chosen to be significant for this period for this patient signal. A program using Matlab (Cf. Appendix) was used to show the details of the maximal signal at the scale at which it is present. Patterns of alpha activity which are not always visible in the main signal show up better in the time course plot at the resolved (maximal) scale.

**Example 1**
This is taken from a short segment of the patient’s inter-ictal record. The segment was taken from leads F1-F2 and shown in fig. 3(a) below. The actual Fourier Spectrum is in (b), indicating good alpha activity around 12 Hz. To show out this clearly, using DB6 Wavelet (Cf. Section 4.1), the spectrum is shown in Fig (c) for this scale. The program using Matlab is given in the appendix.

Good localization and frequency selectivity are noted in fig.(c). The variation of alpha activity in a slow pattern is noted which is not that clear in fig.(a), the original signal.

A Fourier component at this 11 Hz will only indicate a constant amplitude and not show the variations. Since the wavelet looks for a band (of frequencies) near the chosen point frequency, it is able to show the variations. The Fourier spectrum looks *merely at that* frequency, while wavelet looks a little wider. The frequency analyzer plot gives the Fourier spectrum of the signal over a time window (fig.3b). Suppose we take a 5 sec interval plot and do a F.T. This would indicate the presence of peaks
Fig. 3: The EEG, its spectrum and the wavelet (DB6) decomposition at level 6, corresponding to a frequency of 11 Hz. The X axis is in time, milliseconds for top and bottom figures.

In this, the entire plot of the Continuous wavelet transform (CWT) in scalogram (fig.3) is observed for local peak regions on the computer. (not shown here). This is useful when a quick instant observation of the large time course of signal is to be taken. We may take about 8000 or much more data samples of the EEG, over a time of 30 seconds, perform a CWT analysis with an optimal wavelet (Sec. 4.2) chosen. The intensity plot shows the region of maximal activity. Fig.4 just shows a very short sample of the same.

From the total scalogram plot, regions are marked for closer observation, like the one in fig.4. The wavelet transform is taken at different scales and the scale at which the peaks are maximal in these regions is selected. Then, the signal at this scale is plotted. This is what is shown in fig.3 bottom). In this illustration, the maximum wave peaks were present at scale 6. The wavelet used here is DB6. This is the method that proved helpful in identifying activity in the long record which is worthy of details observation by the clinician. This method is useful in patients having short and sudden outbursts of alpha or spike and wave activity amidst a long quiet interval.

In the scalogram, once we identify the region of outburst of a spike or spike cum wave pattern, we can get its spectral content in the form of a plot which shows the scale on the X-axis and the intensity on the Y-axis. This helps in examining different parts of the record for identical patterns to assess if the even is of a single focus or random. In case of trauma of specific injury, the patterns will be almost same. In epilepsy, it is not true.

EEG-wavelet transform based signal processing
Choosing the appropriate wavelet for a signal is important if the details are to be clearly and correctly represented. That depends on what kind of signal it is, of what oscillatory components it is made up of and so on.

Choosing among several wavelets The Fourier transform provides an infinite number of frequencies of any signal. We can reconstruct the signal back from the frequencies using the inverse transform. This property of reconstruction is possible if the function possesses orthogonality. The sinusoidal waves are orthogonal. Likewise, certain wavelets have orthogonality. But unlike the sinusoidal function which exists for all time, the wavelet is short and is said to have a compact support. Just as sine functions have harmonics, there are higher frequency components for a wavelet. It is the total combination of such components that we get when perform a wavelet transform of a signal. The concept of scale is introduced in wavelets, which is the reciprocal of the usually employed term frequency in Fourier analysis. A higher scale means a lower frequency wavelet.

Wavelets Fig. 4. Scalogram shows the wavelet coefficients as intensity plot which possess orthogonality are the Daubechies series of wavelets named as DB4, DB6 etc., where the numbers 4 and 6 mean the range of support. A DB6 pattern and DB4 are shown below for comparison. The same wavelet function is used for reconstruction in these wavelets. In yet another class of wavelets called biorthogonal wavelets, there are two functions, one for splitting the signal into wavelet coefficients and another for reconstruction. The biorth.3.7 wavelet is having three taps for the forward seven for the reconstruction wavelet.

Thus wavelets can be noted as short segments of signal patterns. The general EEG signal is supposed to be composed of such segments of wave patterns of various scales, and the amplitudes of such scales are totally shown in a scalogram.

Picking the optimal wavelet
Fig. 5: Showing the wavelets for Db4 and Db6

Fig. 6: Showing the wavelets for biorthogonal 3.7 type wavelet – one for decomposition and the other for reconstruction. (Here we employ one the first)
The wavelets can be checked for appropriate choice in the case of stochastic signals like that of the EEG through the following principle.

1. Take the Fourier Transform of the Signal;
2. Take the Fourier Transform of the Wavelet Chosen.
3. Find the Cross correlation (c.c) function of the above.
4. Observe if the function is having one or more peaks. Find the peak factor.
5. Compare and pick the wavelet with the maximum value of this factor.
6. Also, the peak value of this function can be noted down for different wavelets.

The peak factors of c.c. functions is indicative of the peakiness of the spectral content of the wavelet spectrum.

The one which gives the max peak factor among these is a suitable wavelet for this signal. For the signal in fig. 3, the bior.3.7 wavelet (fig. 6) gave a c.c. value of 0.64, more than for other wavelets like DB6, and hence it is chosen for displaying the wavelet transform of this signal segment.

The peak factors of c.c. functions is indicative of the peakiness of the spectral content of the wavelet spectrum.

**EEG signal inferences - examples**

**DB6 wavelet chosen for a typical spiky signal**

The first figure 7 shows the EEG of 5 second during inter-ictal activity of a patient. The spectrum of the same is shown in fig.(b). This indicates predominant oscillations of large amplitudes in 12Hz region and 2-3 Hz region. Hence there is considerable neural activity in the a region.

Fig. (7c) shows the wavelet decomposed signal

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![Wavelet shape shown](image1.png)

![Wavelet Scalogram](image2.png)

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**Fig. 6:** (a) Showing the bior.3.7 wavelet used for the previous EEG signal and (b) giving maximal details clearly in the scalogram.
Fig. 7: Figures (a), (b), (c) are the signal, the spectrum (0 to 40Hz) and the sixth scale wavelet decomposition, which is the maximal component scale. This six corresponds to about 12 Hz. The X axis for plot (c) is also time, same as (a) which is 5 seconds for 400 samples.
using a non-linear wavelet (dB6). This plot is picked from the total CWT at the maximum value point chosen form the c-matrix. Comparing the c-values at each of the scales for maximum, it is found that maximum activity is occurring at scale –6 in this figure. Then along that scale, the values of wavelet coefficients is plotted versus time samples, shown in fig.c.

From this figure, it is clear, that the activity is continuously present with a low frequency modulation throughout the time of 5s. The ringing pattern is seen all through but is not visible from the fig.a. Hence, a better diagnosing is easily made from fig.c.

The same is repeated for DB10 and other wavelets are shown in fig.8 for a different patient’s extract from record.

The biorthogonal wavelet gives greatest
amplitude for the signal at the scale of 6. The low frequency modulation is clearly seen.

Spectral plot along the line of maxima

Another method for comparison purposes is to draw the plot of the spectral distribution at any short region of the signal using wavelet coefficients. From the scalogram, the region where bright areas are present can be selected and in this region, a line of maxima is drawn as shown in fig.9 in (c).

In fig.10 is shown another ictal record example where the signal is that of an epileptic patient. The Fourier spectrum shows random pattern over the entire frequency range and is not useful for comparison between sections of the same record or for follow up. The scalogram is visible with regions of high activity and at that point, the line of maxima is found. Along this line, the plot of wavelet coefficients versus scale gives the line of maxima spectrum. As different from fig.9, this is able to give a region of 0.2 (x10) at scale 2. This is useful for comparison purposes rather than the Fourier spectral plot.

Fig. 9 a) a short signal of slow activity. b) Fourier Spectrum showing peaks in the low delta region c) Scalogram for 250 samples with scales from 5 to 60. The line of maxima is drawn as the wavy line d) The wavelet scale spectral plot.

Fig. 10. a) A spikes record. b) Fourier spectrum c) Scalogram showing a line of maxima d) spectrum along line of maxima.
Appendix

Sample matlab program for eeg signal Processing

```matlab
load c:\curve.dat ;% The file 'curve' is an extract from EEG record using
% graphic digitiser
subplot(3,1,1);plot(curve)
curve=curve-mean(curve);
%plot(abs(fft(curve)))
size(curve)
m=size(curve); m1=m(1); m2=fix(m1/10);
m3=m1/2
h=linspace(0,m2,200);
b=abs(fft(curve));
c=cwt(curve,1:256,'db6');
subplot(3,1,2);plot(h,b(1:200));xlabel('Hz');legend('Fourier')
for j(j)=max(c(j,1:m(1)))
end =1:32
c1
%plot(c1)
[y,i]=max(c1)
num2str(i)
legend(num2str('i'),4)
legend(num2str(i),4)
jj=num2str(i)
subplot(3,1,3)
plot(c(i,1:m1));xlabel 'plot at scale marked on top right';legend (jj,0)
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REFERENCES